Mosquito Larva Classification Method Based on Convolutional Neural Networks

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***Abstract*—In Mexico a great number of diseases spread by the mosquitos *Aedes* has been reported. There are some regions on the country that this number is alarming. The spread of this disease becomes a public health problem and the government is worried about this situation and applied some methods for reducing the infection rate. One of principal methods relies on the localization of the mosquito's larvae and then fumigates them. The localization of *Aedes* larvae is accomplished through state programs which take a considerable time, making them not efficient enough. In this paper we propose a novel method based on convolutional neural networks, where a dataset of larva is used in training in order that the machine learns two types of mosquitos, genus *Aedes* and "others" genera. The digital images of larva are processed using a set of machine learning algorithms and as a result, the classification task is done. The proposed method would make the larva identification process more efficient, automatic and faster than the conventional methods, and thus the infection rates would be decrease. The results show a good performance on *Aedes* larva identification, proving that the system can be applied in the real world.**

Keywords—larva; mosquito; classification; convolutional neural networks; Aedes.

I. INTRODUCTION

Recently several diseases such as Dengue Fever (DF), Dengue Hemorrhagic Fever (DHF), Chikungunya (CHIKV) and Zika, are transmitted through mosquitos, this spread of diseases are causing serious problems in human health. The mosquitos of the genus *Aedes*, especially species *Aedes Aegypti* (Fig. 1), is considered as the principal vector of the transmission of these diseases. In Mexico, an important number of patients have been reported during the years 2015 and 2016, as shown by Table I [1-3].

TABLE I. NUMBER OF PATIENTS IN MEXICO DURING 2015 AND 2016 [1]

	DF and DHF	CHIKV	Zika
Number of patients	13,504	13,102	6,393
Death	21	4	0

Fig. 1 The *Aedes Aegypti* mosquito. One of its particularities is the presence of white spots in the body [4].

Almost all these diseases are observed mainly in the tropical zone of Mexico, such as Chiapas, Morelos, Veracruz, Oaxaca, etc, because *Aedes* mosquitos are very common in these areas. However, due to the global climate change in the earth, these types of mosquitos have been observed in non-tropical zone, such as Mexico City.

In the world, due to the constant movement of people, such as travel, trip and migration, many local diseases that were observed only in certain local area, have been expanded in the world. The diseases transmitted by *Aedes* mosquitos, such as Zika, are observed actually in many countries in the world.

The primary strategy for stopping a disease outbreak consists on the prevention and suppression of the vector. In other words, if the main carrier of these diseases, *Aedes* mosquitos, is suppressed, the spread of these viruses will be radically diminished. An effective method to counter-measure the *Aedes* mosquitos is to know its life cycle and apply efficient actions to interrupt it. The *Aedes* mosquito has four phases in its life cycle: egg, larva, pupa and mosquito as shown by Fig. 2. The first three phases are categorized as aquatic phases because they need water to live [4]. Under the favorable condition, the *Aedes* mosquitos can reproduce in only one or two weeks.

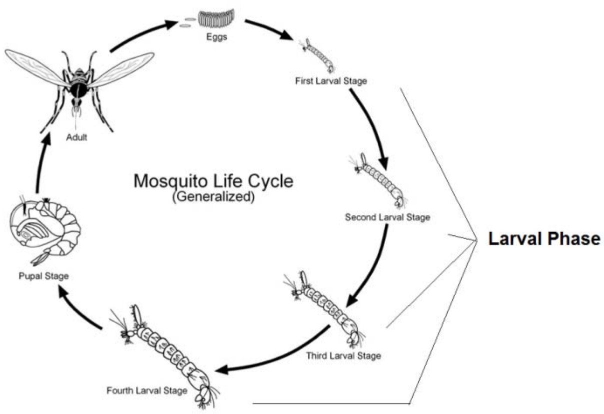

Fig. 2 The Aedes mosquito life cycle [4].

Considering the serious situation in public health caused by the *Aedes* mosquitos, some Mexican local governments apply a methodology to reduce the infection rate of the viruses mentioned above. The methodology relies on the localization of larvae of the *Aedes* mosquitoes, which are based on capturing mosquito larvae in several regions and sending them to the State central laboratory. In the central laboratory, a few specialists classify each one of the great amount of larvae captured from different regions in the State. After the identification of the *Aedes* larvae captured from certain regions, a group of exterminator go to fumigate *Aedes* larvae using insecticides. However, this method is not efficient due to short life cycle of *Aedes* mosquitos, being the case that the larvae have already converted in mosquitos and also have reproduced in other pools. It makes the process of fumigation not efficient enough. Additionally this methodology is very time consuming and tedious.

Taking in account the actual problems that Mexico and many Latin American countries are confronting, in this paper we propose an efficient method to identify larva of *Aedes* mosquitos using convolutional neural networks (CNN) applied to the larva's images captured by mobile devices. In the proposed scheme, the identification process of larvae can be more efficient, automatic and faster than the conventional methodology. Because the identification of the *Aedes* mosquito larvae is carried out in the moment that the larvae are collected, the fumigation process will be more accurate and thus the infection rates would be decreased.

The rest of the paper is organized as follows: in Section II, we explain the data acquisition in detail. In Section III, we present the proposed method for larva image classification. In Section IV the experimental results are presented and discussed, and finally, in Section V, we conclude this work.

II. DATA ACQUISITION

Mosquitoes are insects belonging to the order Diptera and members of a family of the nematocerid flies Culicidae [5]. At least 14 orders of arthropods, containing over 400 different genera and more than 15,000 species, evolved to feed on blood from warm vertebrate animals [6]. Some of these species are more clinically relevant than others because they affect directly the human health. The *Aedes* mosquito is one of most important genus, because it is a principal vector of several diseases mentioned above.

There are different ways to classify mosquitoes, in this work we decide to identify by the larva's eighth (VIII) segment, where we can observe a comb-like figure. The figure 3 shows the image of complete larva and its eighth segment. The form of the comb-like figure can be used to discriminate larvae of the genus *Aedes* from larvae of other genera. For example any larva of *Aedes* has a single row in its comb, while the other genera of mosquitoes have several rows in their comb. In the figure 4, we can observe the different types of combs of four different genera of larvae. To capture correctly the images of eighth segment of larvae, we designed an image acquisition system that consists of a smartphone, a microscope lens and a support for the smartphone. The microscope has amplification capacity of 60-100 times. In figure 5 it is shown our image acquisition system.

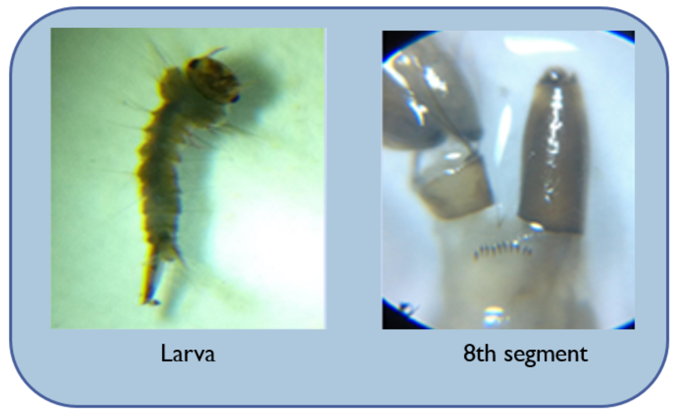

Fig. 3. Image of larva and its 8th segment

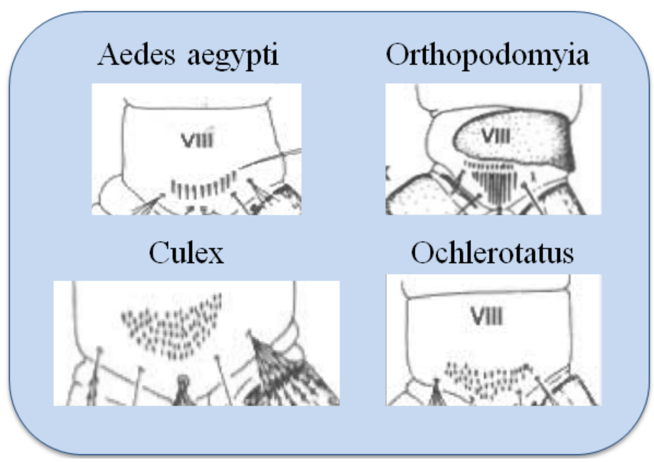

Fig. 4 The eighth segment of larvae of four different genera of mosquitos [5]

Fig. 5 Image acquisition system

Using image acquisition system shown in Fig. 5, we generate the Datasets composed of approximately 300 images of larvae, which are 102 images of *Aedes* and 208 images of "*No Aedes*". All larvae used to generate the Datasets are previously identified and classified in the Public Health Laboratory of Hidalgo State in Mexico. The figure 6 shows two images of eighth segment of tow larvae: the left image belongs to "*No Aedes*" and the right image belongs to the *Aedes* genus.

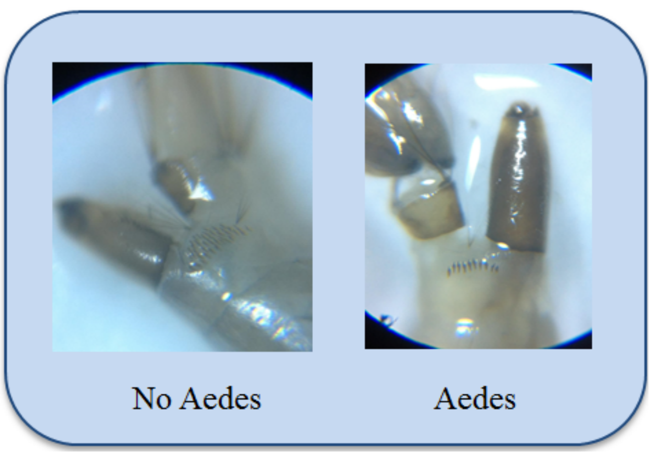

Fig. 6. Two classes of larva

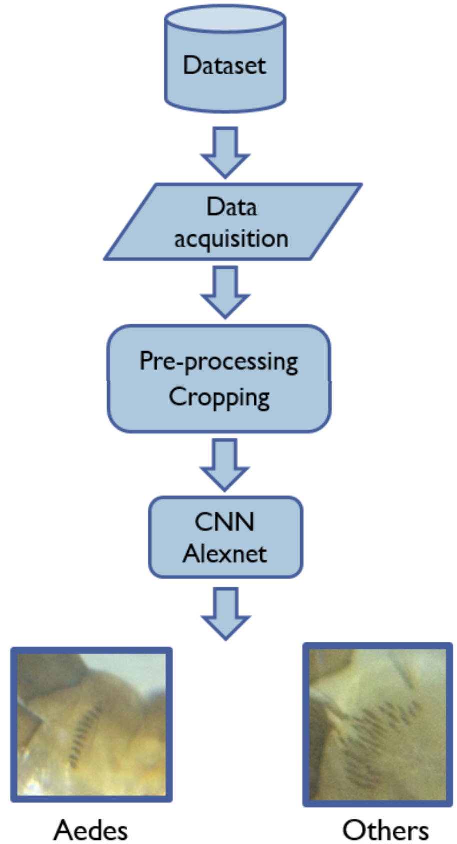

Fig. 7. Block Diagram of the proposed scheme

III. Proposed Method

In this paper we proposed a novel manner to classify the larva's images, which consist of four steps: 1) Data acquisition, 2) Image pre-processing, 3) Training of the CNN and 4) Real Time Classification. The block diagram of the proposed scheme is shown in the figure 7. In this section, we describe last three steps: Image pre-processing, Training of the CNN and Real Time Classification.

A. Image pre-processing

The raw images are not suitable for the training, so it was necessary to carry out pre-processing. Since the images are taken using a microscope lens, there are some regions that are not relevant for the classification purpose. In the following figure, we can observe the pre-processing applied to the dataset. In the pre-processing stage, first input image is converted in binary image using a predetermined threshold value and then several morphologic operations, such as labeling and hole-filling, are applied to the binary image to obtain circular region. The radio r of this circular region is estimated and then the relevant square region with size $2r \times 2r$ is extracted, cropping un-relevant black region.

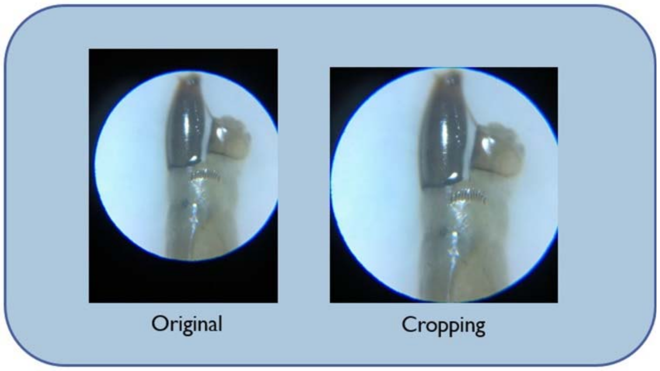

Fig. 8 Result of pre-processing

B. *Training of the CNN*

In this paper we propose a classification method based on the deep learning. The deep learning is a set of machine learning algorithms which try to simulate the human brain behavior. Unlike other machine learning techniques, such as Gaussian Mixture Model (GMM) and Support Vector Machine (SVM), in the deep learning the feature extraction task are performed in layers close to the input layer. So in the deep learning system, the feature extraction process is not required before the training process. In this paper, we used this technique in order to identify the larva of the *Aedes* mosquitos.

In training stage, we used the convolutional neural network called Alexnet, which was the first network that popularized convolutional neural networks (CNN) in computer vision. This network was developed by Alex Krizhevsky, Ilya Sutskever and Geoff Hinton [7]. Alexnet has a very similar architecture to LeNet, however it was deeper and bigger than LeNet, which means that it can describe better the images.

As the network is deeper, we can extract more information from the images. This network relies on eight layers (convolutional, local responses, max-pooling, fully-connected layers), in the figure 9 we can observe the architecture of this network. For the class “*Aedes*”, we used 92 images for training and 10 images for testing; for the class “others” or “No *Aedes*”, we used 198 images for training and 10 images for testing. As cross-validation data, we used the 25% of the training set of each class. When training data is small (like in this case), there is a risk of having overfitting, which means that the network does not learn image features, instead, it only memorizes the training set and, when a new data (unseen by the network) is presented to the network, it can be not classified well. In order to reduce the overfitting, the Alexnet uses dropout technique in the layers FC6 and FC7. As we can see from Figure 10, the difference between the accuracy and the loss of validation is large, which means that there is no overfitting in the training process.

The training was done from scratch (without using pre-trained model). When a dataset is trained from scratch, it requires great number of epochs for the network to converge, in this work, the number of epochs was 200 and we used a learning rate of 0.001.

C. *Real Time Classification*

The raw RGB images, which are pre-processed as describe in III-A, are used as input data and then as we can observe from the figure 7, the image is processed and as output we obtain the FC8 layer, a 2-D vector which contains the probabilities of class belonging, thus, this layer were used for the classification task.

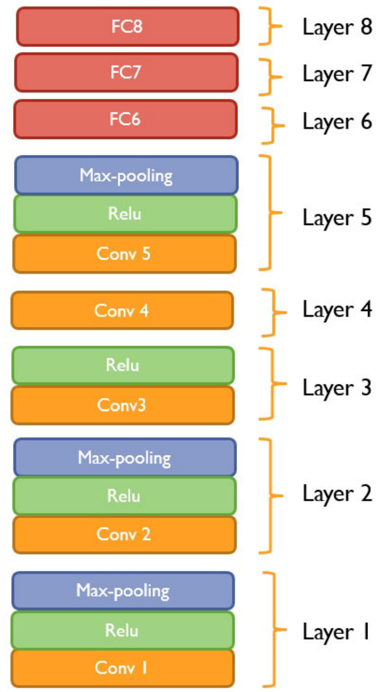

Fig. 9. Alexnet architecture

IV. Experimental Results

We performed the experiments using different numbers of epochs for training. For example, using number of epochs is equal to 30, 50 and 100, the network could not learn well the characteristics from the images of larva. The accuracy was around 70% and the validation loss and the training loss ware quite high. This is because that the training was from scratch and it was necessary to do a great number of epochs in order to increase the accuracy and reduce the loss to the minimum.

Using a great number of epochs such as 200, the network could achieve 96.8% of accuracy and both the validation loss and training loss are reduced up to around 20 and 10, respectively. After the training, we obtain a model which we can use for the classification task. In the figure 10 we can observe the accuracy of the training using the validation and training images. We can observe from this figure, after 40 epochs, the CNN begins to learn correctly, reducing the training and validation errors and at same time increasing the learning accuracy. After approximately 180 epochs, the CNN becomes converged.

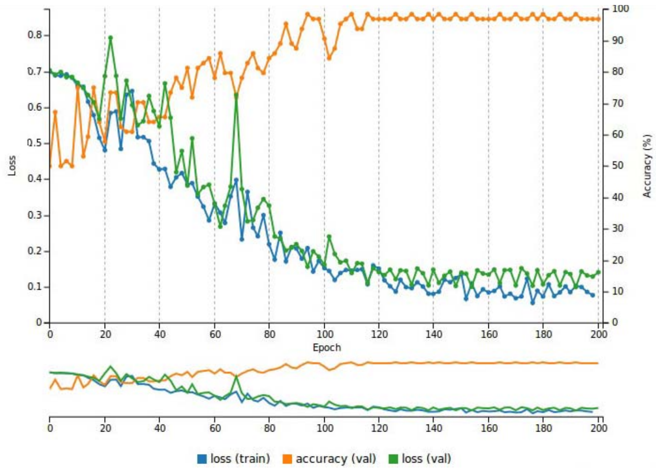

Fig. 10 Training process that shows CNN accuracy and both training loss and validation loss.

TABLE II. AEDES CLASSIFICATION RESULTS

Aedes Image	Classification	
	Aedes	*Others*
Img1	**90.17%**	9.83
Img2	**99.8%**	0.2%
Img3	**99.7%**	0.3%
Img4	**99.68%**	0.32%
Img5	**87.99%**	12.01%
Img6	**98.47%**	1.53%
Img7	**97.42%**	2.58%
Img8	**96.99%**	3.01%
Img9	**98.7%**	1.3%
Img10	**99.95%**	0.05%
Average	**96.88%**	3.12%

TABLE III. "OTHERS" CLASSIFICATION RESULTS

Others Image	Classification	
	Aedes	*Others*
Img1	45.08%	**54.92%**
Img2	**96.9%**	3.1%
Img3	18.17%	**81.83%**
Img4	2.44%	**97.56%**
Img5	12.2%	**87.8%**
Img6	**85.87%**	14.13%
Img7	7.66%	**92.34%**
Img8	3.09%	**96.91%**
Img9	14.29%	**85.71%**
Img10	**64.84%**	35.16%
Average	35.05%	**64.95%**

For testing the system, we choose a set of 10 different images for each class, which were not used in the training stage. The results are shown in the table II and III.

From the table II and III we can observe that the system is capable to recognize the larvae of *Aedes* mosquitos with an accuracy of approximately 96.88% in average. On the other hand, the accuracy for the "others" class classification was 64.95%.

The results show that the false negative error for Aedes classification is 0.0%, on the other hand, the true negative rate, where other larvae are classified erroneously as Aedes larvae, is 70%. For practical purposes, the obtained results are very good taking into account that the objective of the proposed method is to correctly identify the larvae of *Aedes* mosquitos. The results show that it is suitable to implement this system in a mobile device, equipped with a microscope camera for *Aedes* larva classification in field works, and thus, the localization of this vector could be more accurate and the process of fumigation would be more efficient. As a benefit of this efficiency, the infection rate would be decreased.

V. CONCLUSIONS

In this paper we proposed a novel method based on convolutional neural networks (CNN) for the larva image classification in order to identify larvae of genus *Aedes* mosquitos. The proposed scheme provides a high identification rate of the *Aedes* larvae, giving false negative error rate is 0% and true negative rate is 70%. However, we consider that the proposed system is suitable for fast identification of the *Aedes* larva in the field work. It makes efficient elimination of *Aedes* mosquitos which are considered as an important vector of several diseases. Using the proposed system, the persons who capture larvae of mosquitos in several regions, can identify the larvae of the *Aedes* mosquito in this moment and eliminate them before the larvae become into mosquitos.

The principal reason of the still poor performance in true for "others" classification in the proposed system is that the amount of images used for training stage is very small. It is a well-known issue of the deep learning, that a great amount of training data is required to obtain a better performance. In this paper we worked only 310 images, 102 images of *Aedes* and 208 images of "others" larvae due to the availability in this moment. We consider that the performance of the proposed system will be improved if we can use sufficient amount of images of larvae of both classes to train the CNN using deep learning algorithm. In this situation, we can use this proposed system as a pre-trained model in order to reduce the training time and obtain much better performance.

As future works, we consider that the other types of pre-processing, such as the use of the Gabor Filtering and/or the Total Variation algorithm in order to focus only in the comb-like figure of the eighth segment of larvae, which is the principal identifier of the *Aedes* larva, the performance of the proposed scheme can be improved. Also we consider that the use of different architectures of the CNN, such as Siamese network and triplet network architectures can be improved the classification performance.

ACKNOWLEDGMENT

Authors thank Dr. Antonio Arista-Vivero, infectious disease physician for important advises about diseases transmitted by *Aedes* mosquitos, as well as the Public Health Laboratory of Hidalgo State in Mexico for identified larvae of several genera of mosquitos.

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